

Figure 1.

Number of Jan. 2015- Nov. 2016 Flash Flood Events

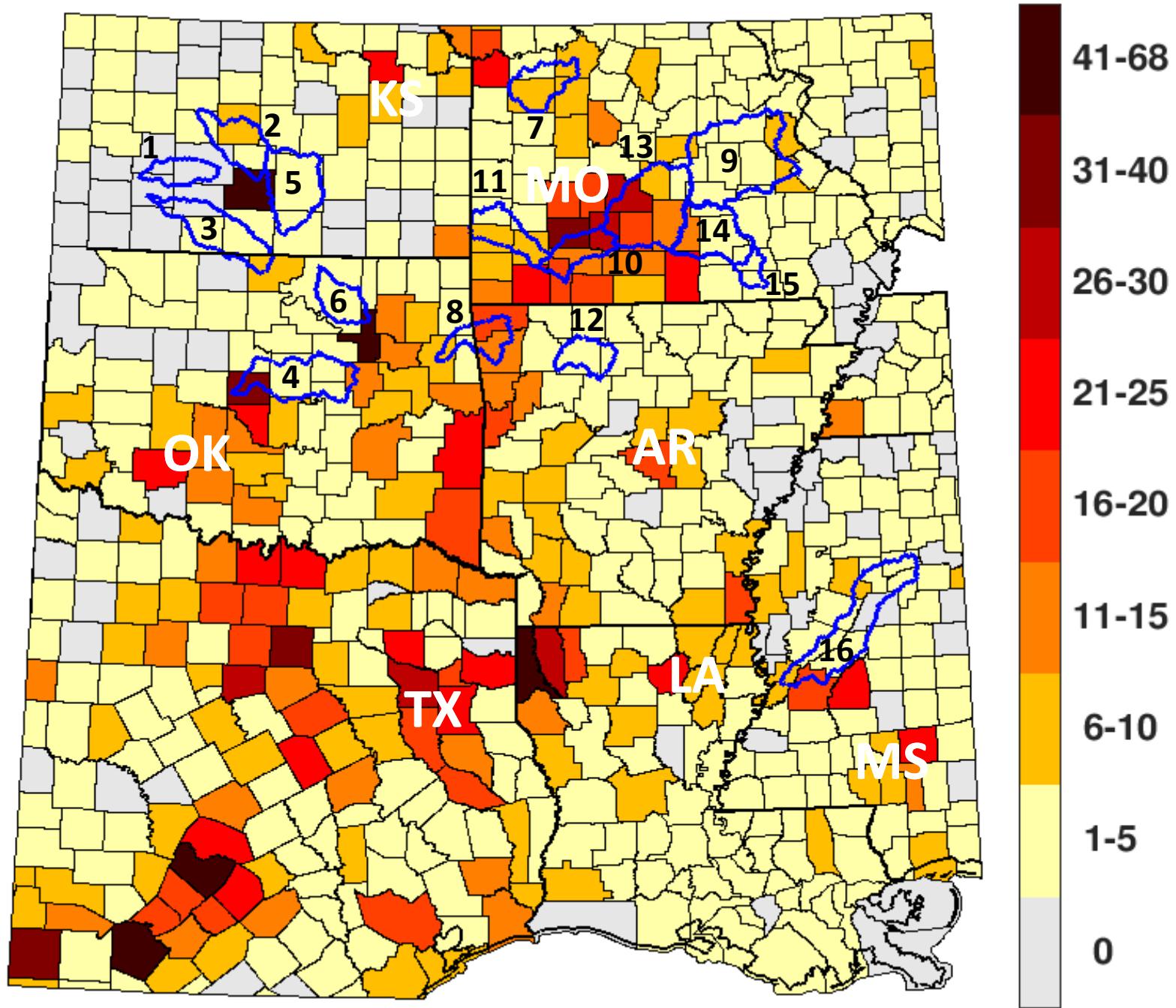


Figure 2.

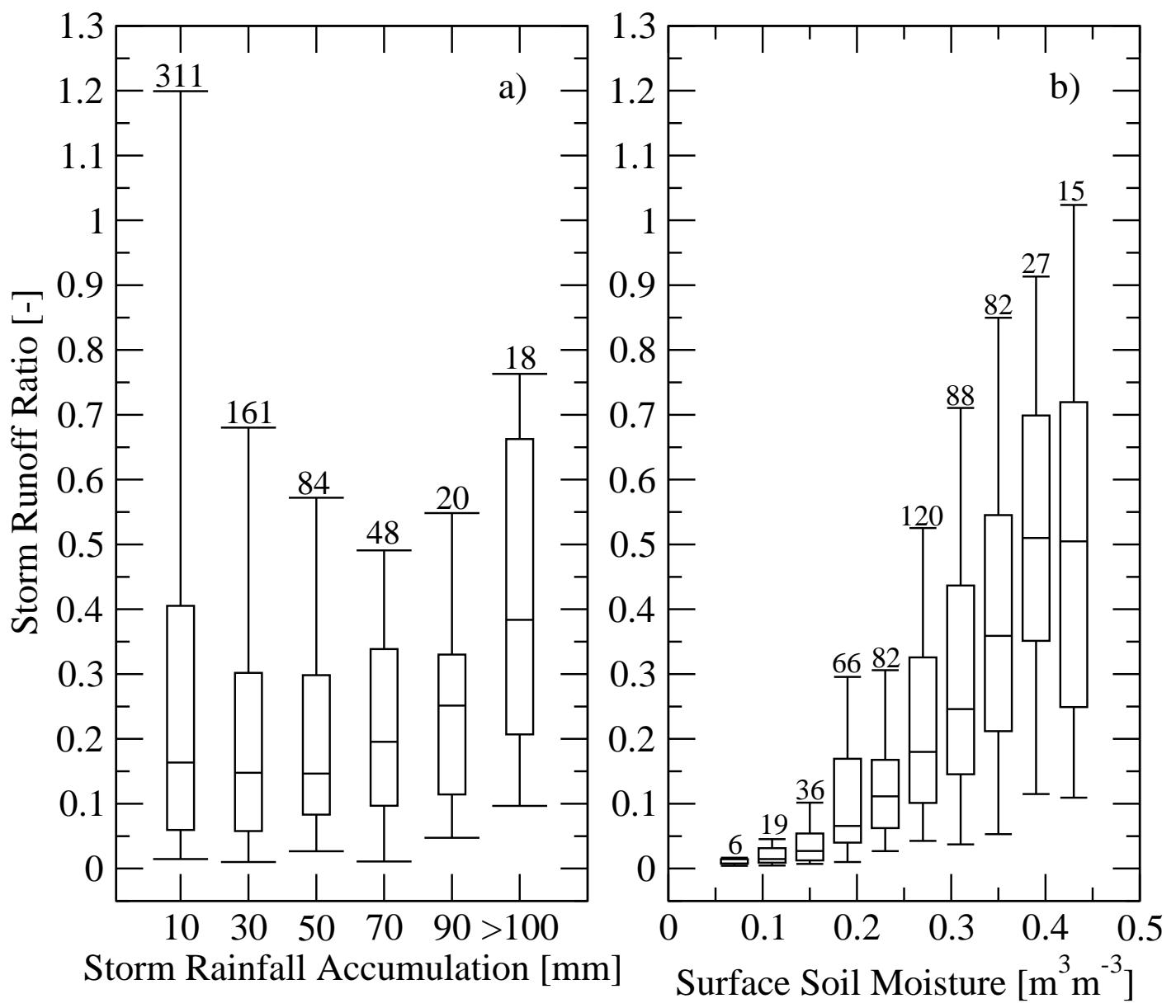
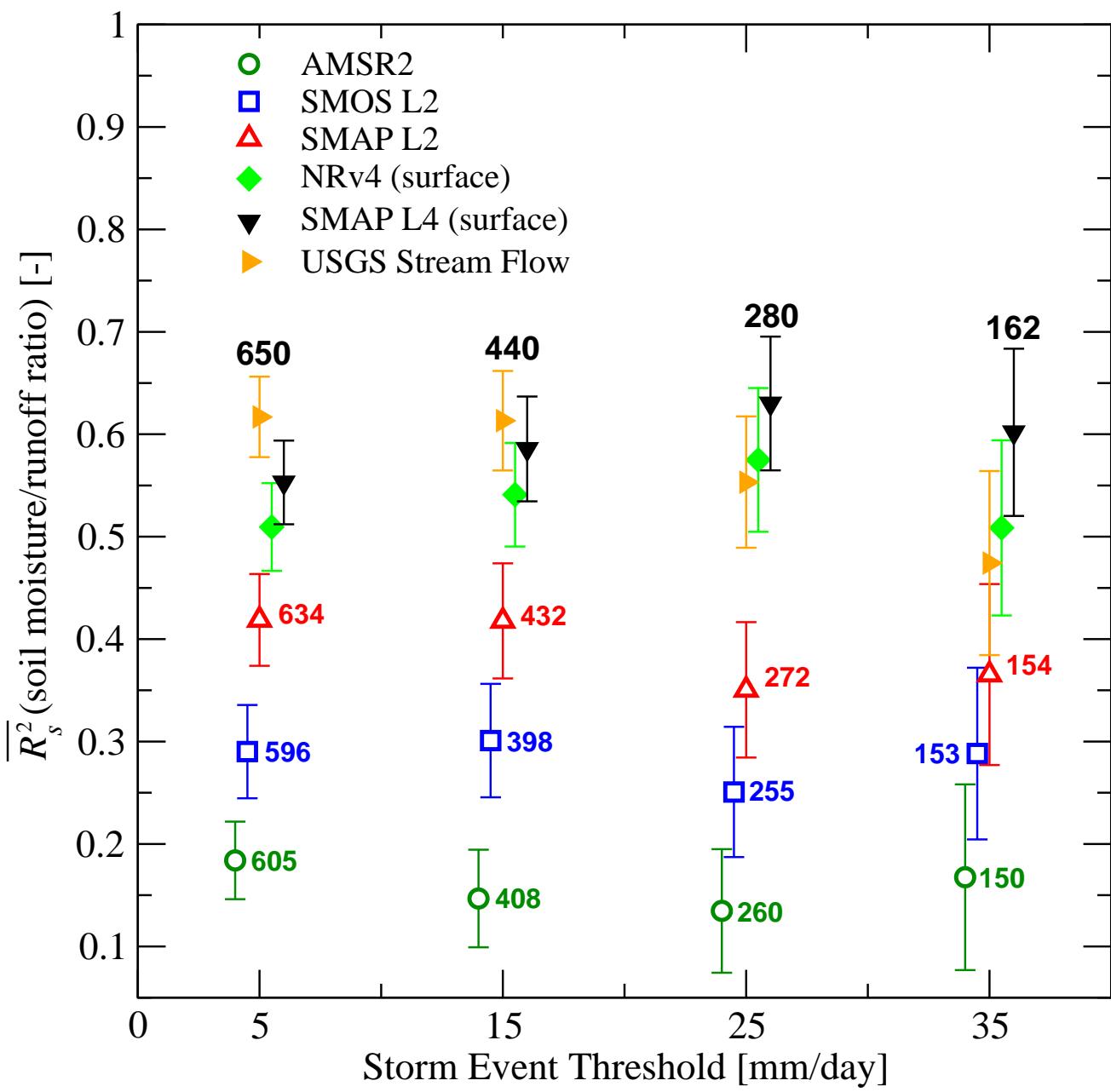


Figure 3.



1 **L-band microwave remote sensing and land data assimilation improve the representation**
2 **of pre-storm soil moisture conditions for hydrologic forecasting**

3
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8
9 **Abstract**

10 Recent advances in remote sensing and land data assimilation purport to improve the quality of
11 antecedent soil moisture information available for operational hydrologic forecasting. We
12 objectively validate this claim by calculating the strength of the relationship between storm-scale
13 runoff ratio (i.e., total stream flow divided by total rainfall accumulation in depth units) and pre-
14 storm surface soil moisture estimates from a range of surface soil moisture data products. Results
15 demonstrate that both satellite-based, L-band microwave radiometry and the application of land
16 data assimilation techniques have significantly improved the utility of surface soil moisture data
17 sets for forecasting stream flow response to future rainfall events.

18
19 **1. Introduction**

20 Anticipating the capacity of the land surface to infiltrate future rainfall is an important source of
21 predictability in short-term operational stream flow forecasts [Silvestro et al., 2014; Massari et
22 al. 2014]. Dynamic changes in this capacity are due primarily to variations in soil moisture
23 content, which determine the infiltration capacity of the soil column [Western and Grayson,

24 1998]. As a result, there has been considerable interest in using remotely-sensed surface soil
25 moisture retrievals for improved monitoring of pre-storm soil moisture conditions within
26 hydrologic basins [Massari et al., 2015a]. However, these retrievals suffer from a number of
27 well-known weaknesses including: 1) coarse spatial resolution (typically > 30 km), 2) shallow
28 vertical support within the soil column (typically 1-5 cm), and 3) reduced accuracy under dense
29 vegetation.

30

31 Therefore, robust evaluation techniques are needed to objectively measure the benefits of new
32 soil moisture products for hydrologic forecasting. One common approach has been to compare
33 hydrologic model performance before and after the assimilation of a remotely-sensed soil
34 moisture product. However, a review of these approaches reveals a wide disparity in conclusions
35 regarding the value of soil moisture assimilation for forecasting stream flow [Crow and Ryu,
36 2008; Massari et al., 2015b; Lievens et al., 2015]. This lack of consistency arises, at least in part,
37 from significant sensitivity to the structure and calibration of the particular hydrologic model
38 applied in the assimilation system [Chen et al., 2009; Zhuo and Han, 2016; Massari et al.,
39 2015a]. Therefore, evaluation results are non-robust in that they are affected by the accuracy of
40 the assumed parametric relationship connecting precipitation, runoff and soil moisture imbedded
41 within these models. In order to remove this sensitivity, and provide a more robust basis for
42 cross-comparing a wide range of soil moisture products, Crow et al. [2005] developed a
43 simplified evaluation approach based on temporally sampling the Spearman rank correlation
44 between pre-storm soil moisture and (subsequent) storm-scale runoff ratios – defined as the ratio
45 of total storm-scale stream flow to total storm-scale rainfall accumulation (both in dimensions of
46 length) over a ~1 week period following a triggering precipitation event.

47

48 There has been considerable recent progress in the development of operational soil moisture
49 products. These advances include the 2009 launch of the European Space Agency Soil Moisture
50 and Ocean Salinity (SMOS) mission [Kerr et al., 2010] and the 2015 launch of the National
51 Aeronautics and Space Administration Soil Moisture Active Passive (SMAP) mission [Entekhabi
52 et al., 2010], both dedicated to measuring global surface soil moisture using L-band microwave
53 radiometry, as well as the development of operational, value-added soil moisture data products
54 based on the assimilation of L-band observations into a land surface model, such as the SMAP
55 Level 4 Surface and Root-zone Soil Moisture (SMAP_L4) product [Reichle et al., 2016]. Our
56 goal here is to update Crow et al. [2005] to consider these new soil moisture products and
57 provide an objective description of their relative value for hydrologic forecasting.

58

59 **2. Study basins and data**

60 This study focuses on 16 medium-scale (2,000-10,000 km²) hydrologic basins located within the
61 south-central United States (Figure 1). This particular region has experienced an unusually large
62 number of flash flooding events during the past two years (Figure 1) and is therefore a natural
63 choice for an analysis aimed at hydrologic predictability. In addition, land cover conditions in the
64 region are generally amenable to the remote sensing of soil moisture (i.e., there is infrequent
65 snow cover, generally modest topographic relief, and relatively isolated forest coverage). The
66 selection of specific basins within this region was based on a screening analysis performed by
67 the Model Parameterization Experiment [Duan et al., 2006] which identified suitable basins with
68 adequate rain gauge density and lacking significant amounts of anthropogenic impoundment or
69 diversion of stream flow.

70 Individual basin characteristics are summarized in Table 1. Moving from west to east, these
71 basins exhibit progressively higher mean annual rainfall and runoff ratios (Table 1). Western
72 basins are generally characterized by rangeland, grassland and winter wheat land cover types
73 with relatively low biomass. More easterly basins contain larger amounts of upland forest cover
74 and summer agriculture in low-lying areas.

75 For each basin, daily rainfall accumulations are derived from the spatial and temporal
76 aggregation of gauge-corrected, 4-km Stage IV precipitation [Lin, 2011] data (to a daily time
77 scale and a basin-average spatial scale) and daily stream flow values based on United States
78 Geological Survey (USGS) stream gauge measurements located at each basin outlet [USGS,
79 2016]. Rainfall accumulation and stream flow daily totals are computed for 0 to 24 LST (UTC-6
80 hours). Antecedent soil moisture estimates are obtained from each of the sources described
81 below.

82 2.1 AMSR2

83 AMSR2 soil moisture retrievals were based on the application of the Land Parameter Retrieval
84 Model (LPRM) to the ~35-km resolution X-band channel of the Japanese Space Agency
85 Advanced Microwave Scanning Radiometer-2 (AMSR2) satellite sensor to produce a 0.25°
86 resolution product [Vrije Universiteit Amsterdam and NASA GSFC, 2014; Parinussa et al.,
87 2015]. Owing to known problems with LPRM retrievals obtained at the 1:30 PM AMSR2
88 ascending overpass [Lei et al., 2015], only retrievals from the 1:30 AM descending overpass
89 were utilized. In addition, retrievals with uncertainties greater than $0.40 \text{ m}^3 \text{ m}^{-3}$ were masked.
90 These masked retrievals comprise approximately 11% of all AMSR2 retrievals in the study
91 region. The AMSR2 sensor also measures in a (lower frequency) C-band channel which is

92 suitable for retrieving soil moisture; however, this channel is known to be contaminated by radio
93 frequency interference over the United States.

94 2.2 SMOS L2

95 The SMOS mission [Kerr et al., 2010] measures L-band (1.400-1.427 GHz) microwave
96 brightness temperature at ~45-km spatial resolution with equatorial ascending/descending
97 overpasses at approximately 6 am/pm local solar time and a 3-day revisit period at the equator. It
98 began scientific data collection in January 2010. The SMOS Level 2 (L2) soil moisture product
99 utilized here is based on application of SMOS processor version 6.2.0 to retrieve soil moisture on
100 an equal-area ISEA4h9 15-km grid [Kerr et al., 2012]. SMOS_L2 retrievals obtained from both
101 ascending (6 pm) and descending (6 am) orbits were combined into a single time series.

102 Normalized retrieval error was determined by dividing the SMOS data quality index value
103 (provided with each soil moisture value) by the absolute SMOS_L2 soil moisture estimate. All
104 retrievals with normalized error greater than 0.50 [-] were masked from the analysis. These
105 masked retrievals comprise approximately 7% of all SMOS_L2 retrievals in the study region.

106 2.3 SMAP L2

107 Launched in January 2015, SMAP began continuous science data acquisition on March 31, 2015
108 with its L-band (1.41 GHz) radiometer [Entekhabi et al., 2010]. The SMAP Enhanced Level 2
109 (L2) Passive Soil Moisture product is generated by applying the Backus-Gilbert optimal
110 interpolation technique to the original SMAP brightness temperature product and then the SMAP
111 baseline soil moisture retrieval algorithm [O'Neill et al., 2016]. This version of the SMAP_L2
112 product was released in December 2016 and is posted on version 2 of the global cylindrical 9 km
113 Equal-Area Scalable Earth (EASEv2) grid [Brodzik et al., 2012] with a native resolution of ~36
114 km. Retrievals obtained from both ascending (6 pm) and descending (6 am) orbits were

115 combined into a single time series. Masking was applied to remove retrievals during periods of
116 snow cover or frozen soil.

117 **2.4 SMAP L4 and NRv4**

118 The SMAP_L4 algorithm is an ensemble-based assimilation system built around the NASA
119 Goddard Earth Observing System version 5 (GEOS-5) Catchment land surface model [Koster et
120 al., 2000]. Its primary drivers are SMAP brightness temperature observations and surface
121 meteorological forcing data from the GEOS-5 atmospheric assimilation system, corrected with
122 precipitation observations [Reichle and Liu, 2014]. The algorithm interpolates and extrapolates
123 information from the SMAP observations in time and in space based on the relative uncertainties
124 of the model estimates and the observations. SMAP_L4 data include 3-hourly soil moisture
125 estimates for the “surface” (0-5 cm) and “root zone” (0-100 cm) layers on the 9-km EASEv2 grid
126 [Reichle et al., 2016]. L4 data are available within 2-3 days from the time of observation. The
127 unpublished Nature Run, version 4 (NRv4) data are also generated with the SMAP_L4 system,
128 but configured for a single ensemble member (no perturbations) and without the assimilation of
129 SMAP brightness temperature observations. As a result, NRv4 provides a model-only reference
130 to assess the relative benefit of assimilating SMAP brightness temperature observations.

131

132 **3. Approach**

133 **3.1. Storm event definition**

134 A storm “event” is defined as the 6-day period following a triggering daily precipitation
135 accumulation amount that exceeds a pre-specified threshold. By design, these triggering events
136 always fall on the first day of this event period, and, to avoid the confounding impact of over-
137 lapping storm events, we discard events for which another storm exceeding the threshold occurs

138 within the event period. Likewise, all events must be preceded by at least one day with a daily
139 precipitation amount below the storm accumulation threshold. All daily soil moisture products
140 are 0 to 24 LST (UTC-6 hours) averages, and pre-storm antecedent soil moisture is defined as
141 the minimum value of daily soil moisture obtained during the two-day period prior to the onset
142 of a storm event. In all cases, at least 25% spatial coverage is required to sample a basin-average
143 soil moisture value.

144

145 Daily stream flow observations (in native flow rate dimensions [L^3/T]) are converted into daily
146 depths [L/T] via normalization by basin area. Daily rainfall and stream flow accumulations are
147 then temporally summed for each storm event and a storm-scale runoff-ratio is calculated for
148 each individual event. For a range of daily precipitation storm event thresholds, the Spearman
149 rank coefficient of variation (R^2_s) between antecedent soil moisture and storm scale runoff-ratio
150 is sampled in time for each basin and each soil moisture product. Rank correlation is used
151 because the relationship between antecedent soil moisture and runoff ratio is potentially
152 nonlinear. Owing to the relatively short length of the SMAP data record to date, sampled R^2_s
153 values for individual basins are subject to large random sampling errors, and we currently lack
154 the statistical power to evaluate soil moisture product performance on a basin-by-basin basis.
155 Therefore, we focus only on spatially-averaged values of R^2_s ($\bar{R^2_s}$) acquired across all 16 basins
156 between 31 March 2015 and 31 December 2016.

157

158 No attempt was made to isolate storm flow within the overall stream flow time series. Therefore,
159 it is possible for base flow to contribute a non-insignificant fraction of observed storm-scale
160 stream flow response (especially for low storm precipitation thresholds within relatively humid

161 study basins). However, it should be stressed that the presence of base flow does not undermine
162 the interpretation of $\overline{R_s^2}$ as a metric for stream flow forecasting skill. Instead, it simply indicates
163 that a fraction of this forecasting skill is due to the temporal persistence of elevated base flow
164 levels (associated with high soil moisture values) rather than the prediction of land surface
165 response to future precipitation.

166 3.2. Uncertainty description
167 Uncertainty intervals for R_s^2 values sampled within individual basins are obtained using a 5000-
168 member boot-strapping approach and then merged to estimate uncertainty intervals for sampled
169 $\overline{R_s^2}$. Based on the averaged spatial correlation sampled between SMAP_L4 basin-averaged,
170 surface soil moisture values (presumed to be the most accurate representation of soil moisture
171 available), and the approach of Bretherton et al. [1999], the 16 basins in Figure 1 contain only
172 7.4 spatially-independent samples. In addition, since $\overline{R_s^2}$ values for each soil moisture product
173 are sampled from a highly-overlapping set of storm events, uncertainty intervals attached to
174 individual products provide a potentially misleading description of the statistical significance of
175 pair-wise differences (since the cross-correlation of sampling errors ensures that the variance of
176 sampling error in pair-wise differences is less than the sum of the sampling error variances for
177 each product individually). Therefore, we further assess the sampling uncertainty in relative
178 comparisons based on the boot-strapping of pair-wise $\overline{R_s^2}$ differences between all soil moisture
179 products - considering only storm events whose antecedent conditions are captured by both
180 members of the soil moisture product pair.

181

182 **4. Results**

183 Based on sampling across all storm events and all basins, Figure 2 illustrates the range in
184 observed rainfall runoff ratio and its variation as a function of both storm-scale precipitation
185 accumulation (Figure 2a) and pre-storm surface soil moisture (acquired from the SMAP_L4
186 product; Figure 2b). As expected, a slight increase in runoff ratio is seen with increased storm
187 size in Figure 2a. However, even for relatively large storm events (with > 100 mm of total
188 rainfall accumulation), a wide range of potential storm-scale runoff ratios is observed (Figure
189 2a). Runoff ratio exhibits a much stronger overall relationship with pre-storm surface soil
190 moisture levels (Figure 2b; provided again by SMAP_L4) - demonstrating the contribution of
191 antecedent soil moisture conditions to hydrologic predictability.

192

193 Figure 3 plots $\overline{R_s^2}$ for precipitation storm thresholds ranging from 5 to 35 mm/day and pre-storm
194 soil moisture products. Recall that $\overline{R_s^2}$ is the spatial average of R_s^2 sampled individually within
195 each of our 16 study basins. Numerical labels in Figure 3 reflect the number of storm events
196 sampled to acquire plotted values of $\overline{R_s^2}$. The error bars in Figure 3 capture 95% sampling
197 confidence intervals obtained from the boot-strapping approach described above. However, for
198 reasons discussed above, the pair-wise hypothesis tests presented in Table are used as basis of
199 formal conclusions regarding the statistical significance of sampled $\overline{R_s^2}$ differences between
200 products.

201

202 Higher values of $\overline{R_s^2}$ in Figure 3 are consistent with an enhanced ability to detect variations in soil
203 moisture which subsequently impact stream flow response to future precipitation. Among the
204 remote sensing products (open symbols in Figure 3), SMAP_L2 demonstrates the best $\overline{R_s^2}$ results,
205 followed by the SMOS_L2 product, and then the X-band AMSR2 retrievals. For the lower

206 accumulation thresholds (5, 15 and 25 mm/day), both SMOS_L2 and SMAP_L2 differences
207 versus AMSR2 are statistically-significant (two-tailed, 95% confidence; Table 2). Restricting
208 SMAP_L2 and SMOS_L2 retrievals to only the 6 AM or 6 PM overpasses, to better mimic the
209 use of only the 1:30 AM overpass for AMSR2 retrievals, had only a minimal impact on their
210 sampled $\overline{R_s^2}$ results. Therefore, Figure 3 is consistent with the expectation that L-band remote
211 sensing products are more valuable than older products acquired from higher-frequency
212 microwave channels (e.g., X-band). In addition, SMAP_L2 significantly outperforms AMSR2
213 for the highest event threshold and SMOS_L2 for the lower two thresholds (5 and 15 mm/day).
214 However, the $\overline{R_s^2}$ differences between SMOS_L2 and SMAP_L2 become non-significant for the
215 15 and 25 mm/day thresholds (Table 2).

216

217 Despite its relative superiority versus other remote-sensing products, the SMAP_L2 product still
218 lags behind surface soil moisture estimates obtained from the NRv4 modeling system (Figure 3).
219 Nevertheless, improvement relative to NRv4 is seen when SMAP brightness temperature
220 observations (which form the basis of the SMAP_L2 retrievals) are assimilated into the NRv4
221 modeling system to produce the SMAP_L4 product. However, the difference between the
222 SMAP_L4 and NRv4 $\overline{R_s^2}$ falls short of 95% confidence (ranging from between 84% and 91%
223 confidence depending on storm event threshold size - see Table 2). Relatively little difference is
224 found in Figure 3 when switching between the use of surface and “root-zone” SMAP_L4 and
225 NRv4 soil moisture products (not shown). However, this may be simply due to the tendency for
226 the Catchment land surface model (used to generate both products) to exhibit relatively strong
227 vertical coupling between its surface and root-zone soil moisture predictions [Kumar et al.,
228 2009].

229

230 In addition to soil moisture products, Figure 3 also examines the use of pre-storm USGS daily
231 stream flow data as a predictor of storm-scale runoff ratios. If available, antecedent stream flow
232 measurements are generally assumed to be a valuable predictor of future stream flow magnitudes
233 and commonly assimilated into operational hydrologic models – see e.g., Liu et al. [2016].
234 However, for precipitation accumulation thresholds of 15 mm/day and above, the SMAP_L4
235 product outperforms daily USGS stream flow measurements as a leading predictor of storm-scale
236 runoff ratio - at a significance level which reaches 93% confidence for an event threshold of 35
237 mm/day (see Table 2).

238

239 As noted above, several choices underpin our approach for defining discrete rainfall events
240 within a continuous daily rainfall record. In order to determine the impact of these choices,
241 alternative versions of Figure 3 were generated for the cases of: 1) maximum storm lengths of 5
242 and 7 days (versus the default of 6 days), 2) the use of prior day soil moisture to define
243 antecedent conditions (versus the default of using the minimum soil moisture estimated in the
244 two-day period prior to the storm events), and 3) not masking storm events which are interrupted
245 by the onset of another event (versus the default of masking these events). None of these tested
246 variations changed the qualitative relationships summarized in Figure 3. Another concern is the
247 impact of including snow events on the sampling of $\overline{R_s^2}$ for the NRv4, SMAP_L4 and USGS
248 Stream flow results plotted in Figure 3. However, sub-setting these datasets to include only days
249 with SMAP_L2 retrievals (which have passed a frozen soil and snow cover mask during
250 processing) had no discernible impact on results. Alternative versions of Figure 3 for all cases
251 listed above are shown in the supporting material (Figures S1, S2, S3, S4 and S5).

252

253 **5. Summary and Conclusions**

254 Within the range of basins studied here, expectations concerning storm-scale rainfall runoff
255 ratios are strongly conditioned by appropriate knowledge of pre-storm soil moisture conditions
256 (Figure 2b). In addition, the development and application of both L-band radiometry and
257 advanced data assimilation systems have significantly improved the quality of soil moisture
258 information available for this purpose (Figure 3, Table 2). In particular, the assimilation of
259 SMAP L-band brightness temperature data in the SMAP_L4 system results in a surface soil
260 moisture product with the highest hydrologic forecasting skill observed to date, and the
261 SMAP_L4 product provides at least as much predictive skill as pre-storm measurements of
262 stream flow (Figure 3). The relative advantages of the SMAP_L4 product grow as the analysis is
263 focused on larger storm events (see the right-hand-side of Figure 3). It should, however, be
264 stressed that this conclusion is based on a single regional study in an area that is relatively well-
265 suited to the remote retrieval of soil moisture. Follow-on work over a wider range of conditions
266 is needed.

267

268 In closing, it should be noted that the successful application of satellite-based soil moisture
269 products for hydrologic forecasting also depends on their near-real time availability. SMAP_L2
270 products are typically available within 24 hours from the time of observation. SMAP_L4 data are
271 available within 2-3 days because of the latency incurred by the use of gauge-based precipitation
272 inputs. However, several options exist for shortening the latency of SMAP_L2 and L4 products,
273 including the short-term forecasting of SMAP_L2 products based on SMAP-derived loss

274 functions [Koster et al., 2017] and the production of lower-latency SMAP _L4 products using
275 GEOS-5 forcing inputs without the benefit of gauge-based precipitation inputs.

276

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403 **Table 1.** Attributes of study basins in Figure 1.

404

Basin Number	USGS Station No.	USGS Station Name	Basin Size (km ²)	Annual P (mm)	Runoff Ratio Q/P
1	07144780	Ninnescah River AB Cheney Re, KS	2,049	768	0.08
2	07144200	Arkansas River at Valley Center, KS	3,402	842	0.11
3	07152000	Chikaskia River near Blackwell, OK	4,891	896	0.19
4	07243500	Deep Fork near Beggs, OK	5,210	945	0.15
5	07147800	Walnut River at Winfield, KS	4,855	980	0.31
6	07177500	Bird Creek Near Sperry, OK	2,360	1025	0.23
7	06908000	Blackwater River at Blue Lick, MS	2,924	1140	0.29
8	07196500	Illinois River near Tahlequah, OK	2,492	1175	0.29
9	07019000	Meramec River near Eureka, MO	9,766	1187	0.28
10	07052500	James River at Galena, MO	2,568	1255	0.31
11	07186000	Spring River near Wace, MO	2,980	1258	0.27
12	07056000	Buffalo River near St. Joe, AR	2,148	1238	0.37
13	06933500	Gasconade River at Jerome, MO	7,356	1293	0.24
14	07067000	Current River at Van Buren, MO	4,351	1309	0.31
15	07068000	Current River at Doniphan, MO	5,323	1314	0.36
16	07290000	Big Black River NR Bovina, MS	7,227	1368	0.37

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406

407 **Table 2.** The statistical significance of $\overline{R_s^2}$ differences sampled between all potential product
 408 pairs for a range of daily accumulation storm thresholds. Second row indicates $\overline{R_s^2}$ values taken
 409 from Figure 3. Arrows point to the product with the highest $\overline{R_s^2}$ for each pairing. Significance
 410 values are for a two-tailed hypothesis test.

411

412

5 mm/day

	<u>AMSR2</u>	<u>SMOS L2</u>	<u>SMAP L2</u>	<u>NRv4</u>	<u>SMAP L4</u>	<u>USGS SF</u>
$\overline{R_s^2}$	0.18	0.29	0.42	0.51	0.55	0.62
AMSR2		↑ 96%	↑ >99%	↑ >99%	↑ >99%	↑ >99%
SMOS L2			↑ >99%	↑ >99%	↑ >99%	↑ >99%
SMAP L2				↑ 96%	↑ >99%	↑ >99%
NRv4					↑ 92%	↑ 99%
SMAP L4						↑ 95%

413

414

415

15 mm/day

	<u>AMSR2</u>	<u>SMOS L2</u>	<u>SMAP L2</u>	<u>NRv4</u>	<u>SMAP L4</u>	<u>USGS SF</u>
$\overline{R_s^2}$	0.15	0.30	0.42	0.54	0.59	0.61
AMSR2		↑ 98%	↑ >99%	↑ >99%	↑ >99%	↑ >99%
SMOS L2			↑ 99%	↑ >99%	↑ >99%	↑ >99%
SMAP L2				↑ 97%	↑ >99%	↑ >99%
NRv4					↑ 86%	↑ 90%
SMAP L4						↑ 70%

416

417

418

25 mm/day

	<u>AMSR2</u>	<u>SMOS L2</u>	<u>SMAP L2</u>	<u>NRv4</u>	<u>SMAP L4</u>	<u>USGS SF</u>
$\overline{R_s^2}$	0.13	0.25	0.35	0.57	0.63	0.55
AMSR2		↑ 96%	↑ >99%	↑ >99%	↑ >99%	↑ >99%
SMOS L2			↑ 91%	↑ >99%	↑ >99%	↑ >99%
SMAP L2				↑ >99%	↑ >99%	↑ 99%
NRv4					↑ 84%	← 61%
SMAP L4						← 86%

419

420

421

35 mm/day

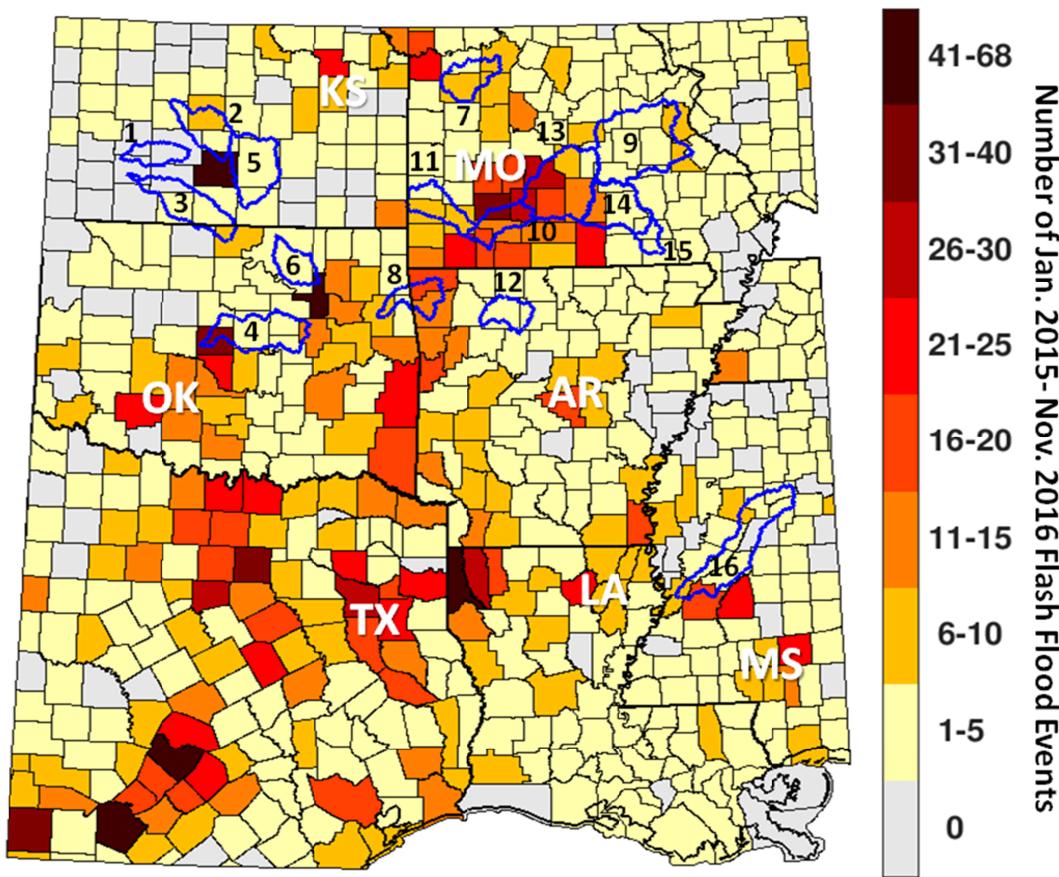
	<u>AMSR2</u>	<u>SMOS L2</u>	<u>SMAP L2</u>	<u>NRv4</u>	<u>SMAP L4</u>	<u>USGS SF</u>
$\overline{R_s^2}$	0.17	0.29	0.37	0.51	0.60	0.47
AMSR2		↑ 78%	↑ 95%	↑ 99%	↑ >99%	↑ >99%
SMOS L2			↑ 71%	↑ 97%	↑ >99%	↑ 95%
SMAP L2				↑ 87%	↑ 98%	↑ 81%
NRv4					↑ 91%	← 65%
SMAP L4						← 93%

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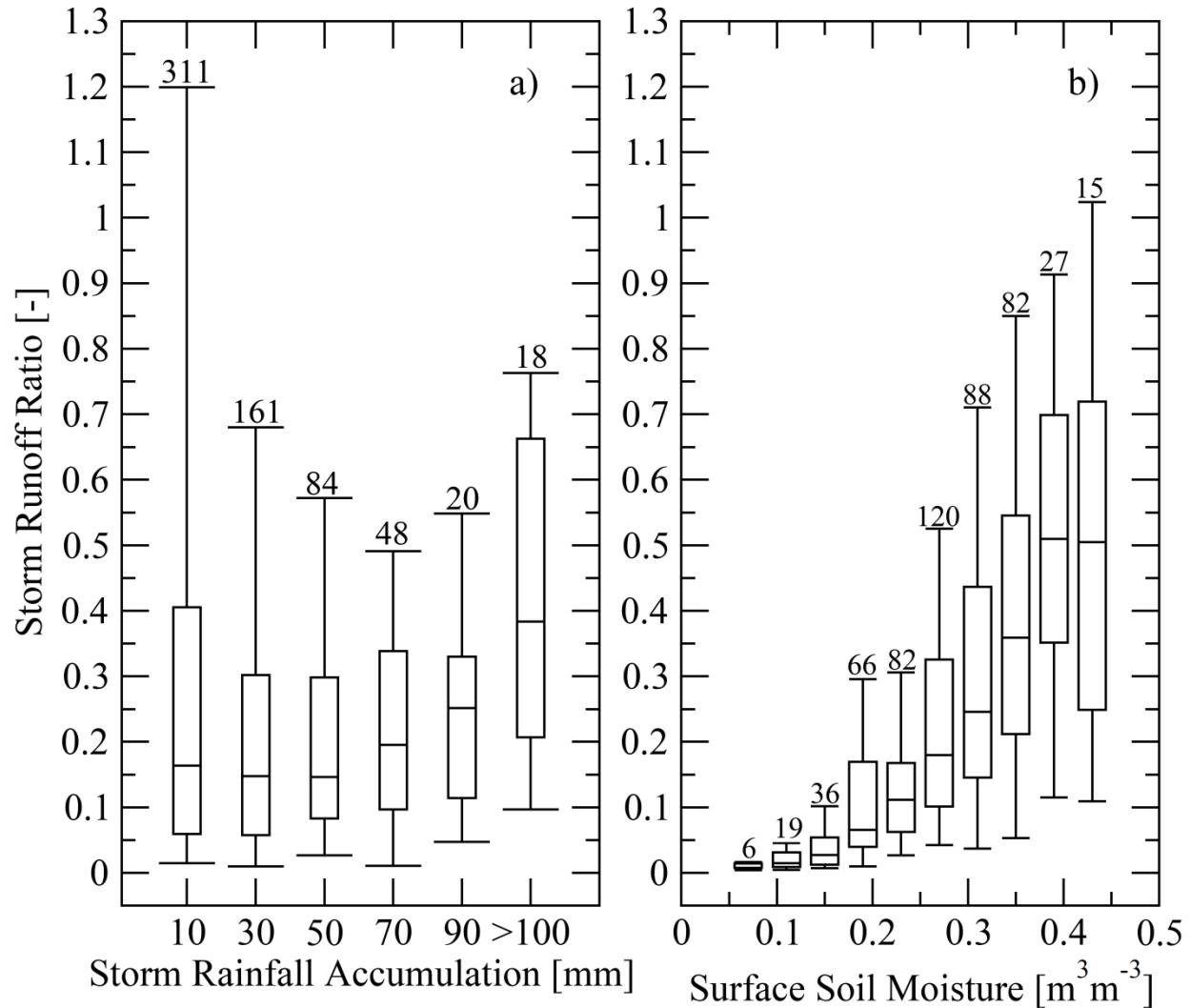
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428 **Figure 1.** For a region of the south-central United States, boundaries (in blue) for our 16
 429 medium-scale study basins overlain on a county-scale map of total number flash-flood events in
 430 the period Jan. 2015 to Nov. 2016. Identification of flash floods is based on the subjective
 431 reporting of major weather events by local weather observers to the United States National
 432 Weather Service (NWS) based on criteria described in NWS [2007]. Basins numbers correspond
 433 in the basin listing order given in Table 1, and individual US states are labeled.
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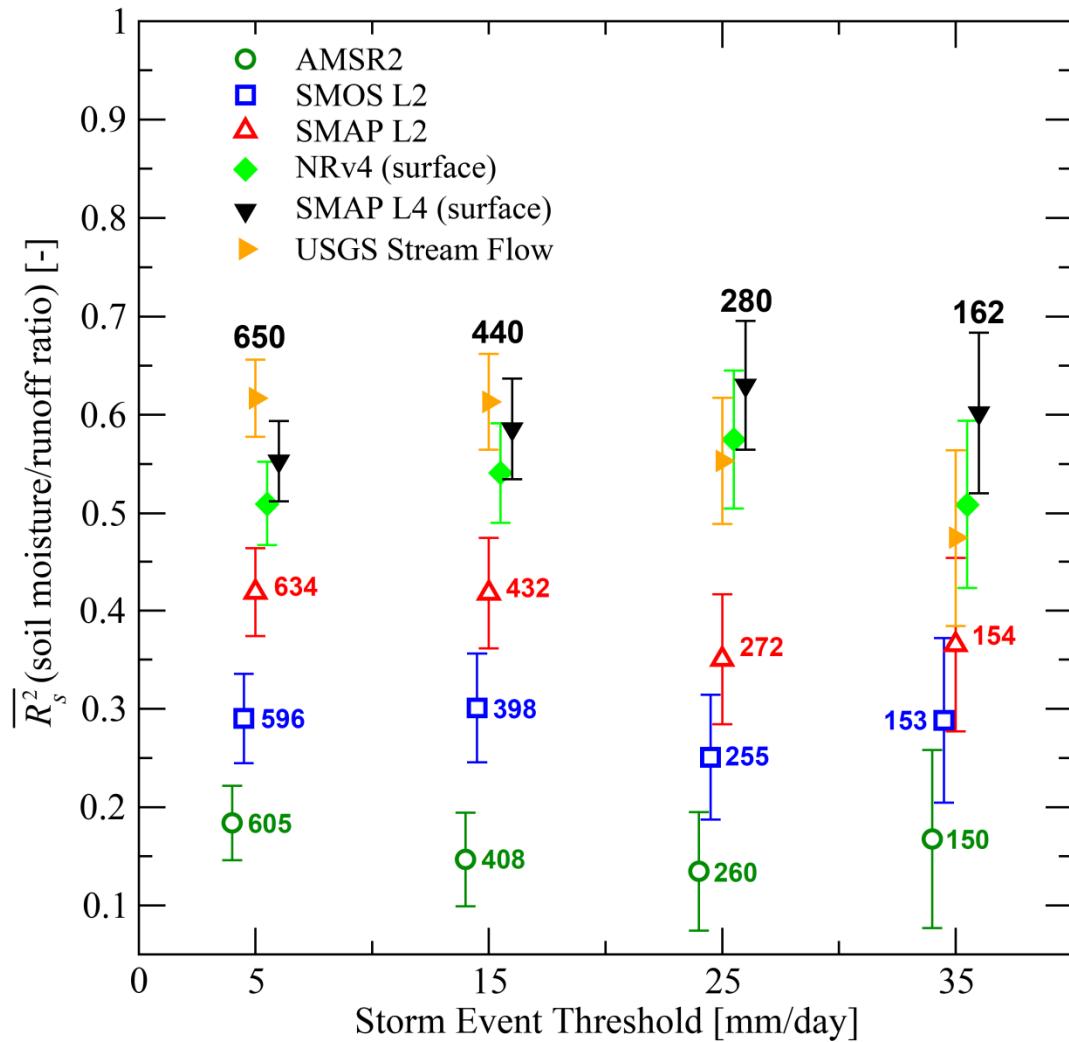
443 **Figure 2.** Box-plots (i.e., 5th, 25th, 50th, 75th and 95th percentiles) of storm-scale runoff ratio
 444 versus: a) total storm rainfall accumulation depths [mm] and b) pre-storm surface soil moisture
 445 [$\text{m}^3 \text{m}^{-3}$] for storm events observed across all basins in Figure 1. In part b), pre-storm surface soil
 446 moisture is based on SMAP_L4 surface soil moisture estimates and events with accumulation
 447 depths less than 10 mm are excluded. Numbers represent total storm events described by each
 448 box-plot. Runoff ratios greater than one likely reflect measurement errors in estimates of storm
 449 total rainfall and/or stream flow used to determine the storm runoff ratio.

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453



456 **Figure 3.** Spearman rank coefficient of variation \bar{R}_s^2 (between pre-storm soil moisture and
457 storm-scale runoff ratio) versus storm event precipitation accumulation threshold for a range of
458 soil moisture products (plus antecedent USGS stream flow). Error bars represent 95% sampling
459 confidence. \bar{R}_s^2 is sampled in time within each basin and averaged across all 16 study basins
460 (Figure 1). Numerical labels reflect the number of total storm events sampled to acquire \bar{R}_s^2 .
461 Symbols lacking individual numerical labels have complete temporal coverage and are based on
462 the storm numbers indicated by the larger black numerals.
463